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Prevention of Work-Related Musculoskeletal Disorders Supported by Artificial Intelligence

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ABSTRACT

In the industry 4.0 era, industrial production is designed to be more efficient, more flexible, and with higher quality. Besides, it is characterized by greater automation and computerization. However, in the industrial field, workers are still involved in many jobs requiring them to lift and move heavy items and other production activities that expose them to the associated risk factors for developing work-related musculoskeletal disorders (WMSDs). In physical ergonomics, studies have shown potential for preventing WMSDs through artificial intelligence (AI). In this regard, this literature review aims to establish the current state of art regarding the use of AI to reduce the risk of developing WMSDs. A literature review was carried out in two databases, and through the combination of keywords, 188 articles were found. Twenty-eight papers were retrieved and analyzed based on dimensions related to WMSDs risk factors, ergonomic criteria, and AI applications.

Keywords: Artificial intelligence, Work-related musculoskeletal disorders (WMSDs), Physical ergonomics

INTRODUCTION

Physical ergonomics is a discipline that considers a human-centric approach to designing a working environment or a job, by adapting work to the worker - the "Fitting the Job to the Worker" concept (Grandjean, 1986).

In the industrial field, workers are still involved in many jobs that require them to lift and move heavy items and in other production activities that expose them to the associated risk factors for developing work-related musculoskeletal disorders (WMSDs). WMSDs are disorders of the tendons, muscles, joints, nerves, and circulatory system that develop over time through overuse and are caused or aggravated by work or the work environment (Nunes and Bush, 2012). In Canada, WMSDs represent 43% of occupational injuries, 43% of compensation costs, and 46% of days lost (AWCBC, 2018). The annual cost of WMSDs to the Canadian economy is estimated to be approximately $8.7 billion (Public Health Agency of Canada, 2018).

Epidemiological studies generally define three groups of WMSD risk factors (Nunes and Bush, 2012): 1) Physical risk factors that include repetitive work, awkward postures, static postures, physical workload, and exposure to vibration; 2) Psychosocial risk factors that relate to the organizational aspects of work such as low decisional latitude and high psychological demands; 3) Individual risk factors about worker sociodemographic profile (e.g., age, gender) or lifestyle (e.g., obesity, level of physical activity).

Preventing risks associated with WMSDs can be accomplished through the ergonomic redesign of the workplace, work processes, and tools. However, this can only be achieved by identifying the risk factors present, which requires collecting and analyzing relevant work data to perform a proper risk assessment. For this purpose, artificial intelligence (AI) is increasingly used and has shown potential in preventing WMSDs, through the analysis of large amounts of human-related data. Due to the development of direct measurement methods, including wearable systems and computer vision-based techniques, new opportunities have emerged for collecting a wide variety of relevant muscular, physiological, and kinematic parameters allowing the acquisition of data related to the workers in an automatic, continuous, and non-intrusive way (De Fazio et al., 2023). For example, wearable devices equipped with sensors and AI algorithms have been used to monitor workers' postures and movements in real-time (Akanmu et al., 2020).

Donisi et al. (2022a) suggested that AI plays an important role in preventing WMSDs by providing early warning of potential problems and providing a more detailed understanding of the factors that contribute to the development of WMSDs. However, more research is needed to understand the effectiveness of AI in this area. In this regard, this paper aims to conduct a narrative review of the scientific literature to answer the following primary research question: "What is state of the art about the application of AI techniques used for the prevention of WMSDs?". In addition, some secondary research questions are defined to assist this literature review: 1) Which AI techniques have been proposed for the prevention of WMSDs purposes in the scientific literature? 2) Which WMSDs risk factors have been evaluated using these AI techniques? 3) Which ergonomic criteria have been at the basis of these AI applications?

METHODOLOGY

The narrative review described in this paper follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Moher et al., 2009). This allowed identify, select, assess, and analyze relevant studies answering our primary and secondary research questions.

Compendex and Inspec were searched for this review from inception to December 2022. Each database was queried using the following keyword structure: ("physical ergonomics" OR "Work-related musculoskeletal disorder") AND ("Artificial Intelligence" OR "Machine learning" OR "Deep Learning" OR "Expert Systems" OR "Fuzzy Logic" OR "Natural Language Processing"). The keywords were searched in the titles and abstracts. A title or abstract that contained one term from each group of keywords was eligible for this review.

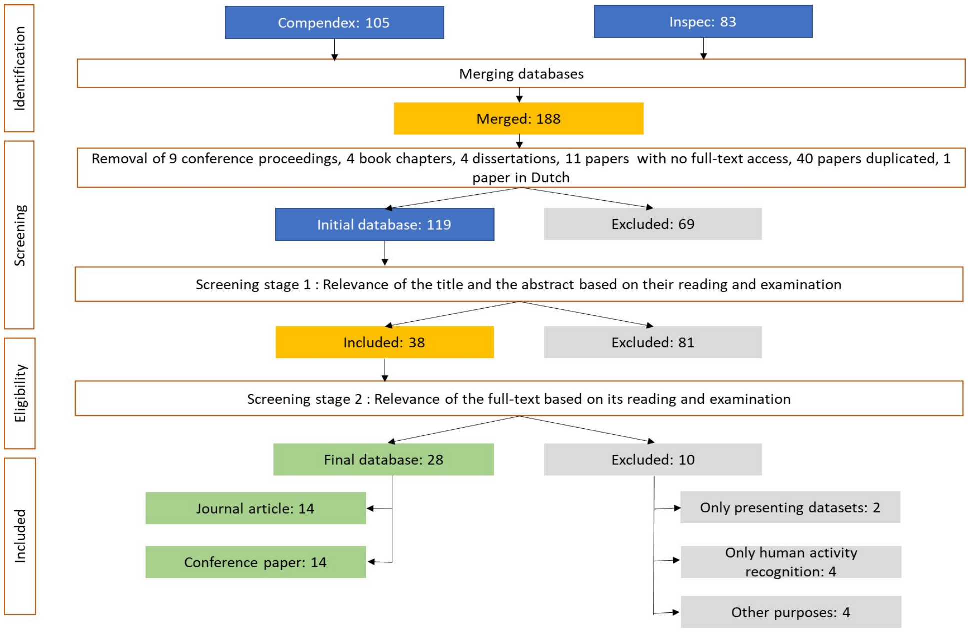

Figure 1: Summary review workflow.

To simplify our research, the exclusion criteria were:

- Conference proceedings, book chapters, and dissertation
- Papers with no full-text access;
- Papers duplicated.

Concerning the screening by title, abstract, and full text, the following exclusion criteria were defined:

- Papers focusing on daily living activities, fitness, sports, athletics, and clinical rehabilitation.
- Papers proposing only frameworks for activity/posture recognition or body angle or joint torque estimation.
- Papers presenting only datasets for working activities/postures.
- Papers that were not relevant or out of scope.

Figure 1 summarizes the PRISMA workflow, the exclusion criteria, and the number of studies included in this literature review.

RESULTS AND DISCUSSION

The narrative review includes 28 papers divided into journal articles (14 out of 28) and conference papers (14 out of 28).

Excluding the current year, over 80% of the studies reviewed (23 of 28) were published in the previous five years (2018–2022). This trend confirms a recent and growing interest in this area of research.

The papers were analyzed according to several categories: WMSDs risk factors and data sources for AI development; principles, methods, standards, and guidelines underlying the ergonomic assessment; AI strategy and algorithms. Table 1 shows the papers in alphabetical order by authors.

- WMSDs risk factors:

In this review, all papers analyzed physical risk factors, and the most frequently assessed factor was the physical workload closely linked to physical fatigue. Recently, AI techniques have been used to classify physical fatigue states and prevent WMSDs. An SVM approach was introduced by Baghdadi et al. (2018) to identify variations in gait parameters recorded by wearable sensors and categorize the states into either fatigued or non-fatigued. In Hernandez et al. (2020), deep learning-based models were used to evaluate the fatigue factor in manual material handling operations using 3D motion capture data. Manjarres et al. (2019) suggested a configuration composed of human activity recognition system and heart sensor to track physical workload.

Other studies have examined body posture as a physical risk factor. Some studies used wearable devices to evaluate the adoption of awkward postures during different tasks. In particular, the IMU sensors by Akanmu et al. (2022) and Villalobos et al. (2022), the insole sensors by Antwi-Afari et al. (2022), and the Flex sensors by Estrada et al. (2020) were proposed explicitly assessing tasks requiring awkward postures. Computer vision for ergonomic-postural assessment is also used for data collection and analysis. Chan et al. (2020) found classification accuracies of 80 to 90% when extracting and using the key joints of the human body and data augmentation. Chatzis et al. (2022) introduced a novel approach based on DL models for action segmentation in RGB-D images and subsequently for predicting the REBA ergonomic risk score during object manipulation actions. Cai et al. (2022) also evaluated the potential WMSDs in the construction sector by using vision-based extracted 3D skeletal poses of workers to evaluate the OWAS ergonomic risk score. In their study, Papoutsakis et al. (2022) developed a classification system to analyze posture-related risks based on visual data. Additionally, they assessed the relationship between physical load and heart rate activity.

There have been additional studies that shed light on different risk factors. Nath et al. (2017) developed a model that deploys built-in smartphone sensors and machine learning algorithms to recognize workers' activities, and extract duration and frequency information, to evaluate ergonomic risks associated with each activity. Aiello et al. (2022) combined tri-axial accelerometer data and a machine learning classifier to identify workers' movements and assess the associated vibration risk exposure.

- Ergonomic criteria:

The ergonomic criteria quoted in the reviewed studies were heterogeneous. Some studies referred to the Borg Rating of Perceived Exertion (RPE), which is a subjective scale of perceived exertion used to rate the level of physical exertion during physical activity (Borg, 1970). By using the Borg scale to label gait data, Karvekar et al. (2019) developed machine learning models to classify the individuals' gait into two (no-vs. strong-fatigue) and four levels (no-, low-, medium-, and strong-fatigue). To assess manual lifting tasks, four studies considered the Revised NIOSH Lifting Equation (RNLE), a manual material handling risk assessment method associated with lifting and lowering tasks. Donisi et al. (2022b, 2022c) presented tree-based machine learning algorithms to classify risk according to the RNLE ("No Risk" and "Risk") by combining height, frequency, and weight variables of lifting tasks. Similarly, Zhou et al. (2021) proposed two different risk levels (safe (LI<1); unsafe (LI>1)) determined by the RNLE. They developed a prediction module consisting of a logistics regression model capable of distinguishing the injury risk levels induced by different levels of force exertion in common lifting tasks. Trkov et al. (2022) used RNLE to analyze six lifting activities, to demonstrate the ability of the machine learning classifier.

Two studies (Cai et al., 2022; Hida et al., 2022) used the Ovako Work Posture Analysis System (OWAS) as a reference to classify workers' postures. The OWAS method is used to identify postures that are safe or unsafe and may result in WMSDs.

In this review, another guideline for ergonomics was identified to mitigate the risk of WMSDs, which is proposed by the Occupational Safety and Health Administration (OSHA) (Delp, et al., 2014). Antwi-Afari et al. (2020) assessed the ergonomic risk levels ("Low," "Moderate", and "High") using OSHA standards based on the weight of the object. On the other hand, Nath et al. (2017) evaluated the same ergonomic risk levels by considering the duration and frequency of pushing/pulling, carrying/lowering/lifting activities.

Other studies used different principles, methods, standards, and guidelines for ergonomic risk assessment, in particular: Firmat's score (Manjarres et al., 2019), ISO 5349–2001 (Aiello et al., 2022), ISO 11226–2000 (Antwi-Afari et al., 2021), Key Indicator Method for Manual Handling Operations (KIM-MHO) (Chan et al., 2020), Muri Ergonomic Waste tool (Papoutsakis et al., 2022), Postural Ergonomic Risk Assessment (PERA) (Akanmu et al., 2020), Rapid Upper Limb Assessment RULA (Rivero et al., 2015, Villalobos et al., 2022), Rapid Entire Body Assessment (REBA) (Chatzis et al., 2022).

Few studies did not mention any known ergonomic methodology but proposed specific principles or categories based on experts' knowledge: Estrada et al. (2020), Olsen et al. (2009), and Walsh, et al. (2006) classified the sitting posture as ergonomically correct and incorrect by using wearable sensors. Steiner, et al. (2009) specified different strain classes, and a respective working scenario has been created for each.

- Artificial intelligence strategies:

In the included articles, the distribution of the AI strategies adopted is as follows: fourteen studies applied ML, seven studies applied DL, four studies applied both ML and DL, and three studies applied FL. The most frequently employed algorithms were Support Vector Machines (SVM) and Decision Trees (DTs), followed by Random Forest (RaF), k-Nearest Neighbors (KNN), AB AdaBoost tree, Long Short-Term Memory (LSTM), Linear Regression (LR), Gradient Boosted tree (GBT), Rotation Forest (RoF), Gated recurrent

Table 1. Analysis of the studies included in the review.

Auteurs	Data source for AI development	WMSDs risk factors	Ergonomic criteria	AI strategy (algorithms)
Aiello et al. (2022)	Tri-axial accelerometer	Hand-arm transmitted vibration	ISO 5349 (2001)	ML (KNN)
Akanmu et al. (2020)	IMU sensors	Body posture	PERA	ML (Reinforcement learning algo.)
Ani et al. (2019)	N.S	Physical workload	N.S	FL
Antwi-Afari et al. (2020)	Insole sensors	Repetition	OSHA	ML + DL (DT, RaF, KNN, SVM, ANN)
Antwi-Afari et al. (2022)	Insole sensors	Body posture	ISO 11226 (2000)	DL (LSTM, Bi-LSTM, GRU)
Baghdadi, et al. (2018)	IMU sensors	Physical workload	Borg Rating	ML (SVM)
Cai et al. (2022)	Videos	Body posture	OWAS	DL (LSTM)
Chan et al. (2020)	Videos (public data collection+ recordings)	Body posture	KIM-MHO	DL
Chatzis et al. (2022)	RGB images	Body posture	REBA	DL
Donisi et al. (2022b)	EMG sensors	Physical workload	RNLE	ML + DL (DT, RaF, RoF, AB, GBT)
Donisi et al. (2022c)	EMG sensors	Physical workload	RNLE	ML + DL (DT, RaF, RoF, AB, GBT)
Estrada, et al. (2020)	Flex sensors	Body posture	Experts	ML (DT)
Hernandez, et al. (2020)	HR sensors+ marker-based motion capture	Physical workload	Borg rating	DL (LSTM, GRU)
Hida e al. (2022)	Motion capture system	Body posture	OWAS	ML (KNN, SVM)
Karvekar et al. (2019)	IMU sensors	Physical workload	Borg rating	ML (SVM)
Maman et al. (2020)	IMU + HR sensors	Physical workload	Borg rating	ML (LR, SVM, RaF)
Manjarres et al. (2019)	HR sensor	Physical workload	Frimat's score	ML (RaF, KNN)
Auteurs	**Data source for AI development**	**WMSDs risk factors**	**Ergonomic criteria**	**AI strategy (algorithms)**
Nath, et al. (2017)	Body-mounted smartphone	Repetition	OSHA	ML (SVM)
Olsen et al. (2009)	Inclinometers	Body posture	Experts	ML+DL (AB, SVM, LVQ, KNN, ANN)
Pancardo, et al. (2018)	HR sensor	Physical workload	Borg rating	FL

(Continued)

Table 1. Continued

Auteurs	Data source for AI development	WMSDs risk factors	Ergonomic criteria	AI strategy (algorithms)
Papoutsakis et al. (2022)	RGB video, HR sensor	Body Posture + Physical workload	Muri Ergonomic Waste tool	DL (CNN, RNN)
Rivero et al. (2015)	N.A	Body posture	RULA	FL
Steiner, et al. (2009)	ECG + EMG sensors	Physical workload	Experts	ML (DT)
Trkov et al. (2022)	Insole sensors+ Accelerometers	Physical workload	RNLE	ML (Single DT, KNN, SVM, NB)
Villalobos et al. (2022)	IMU sensors	Body posture	RULA	ML (DT, SVM, RaF, ET)
Walsh, et al. (2006)	Marker-based motion capture system	Body posture	Experts	ML (DT)
Yu et al. (2018)	RGB images+ Insole sensors+IMU sensors	Physical workload	N.S	DL
Zhou et al. (2021)	Videos (body movement/ posture and facial expression)	Physical workload	RNLE	ML (binary LR)

Abbreviations: AB = AdaBoost; AI = Artificial Intelligence; ANN = Artificial Neural Network; CNN = Convolutional Neural Network; DL = Deep Learning; DT = Decision Tree; EAWS = European Assembly Work Sheet; ECG = Electrocardiography; EMG = surface Electromyograph; ET=extremely randomized trees; FL: Fuzzy logic; GBT = Gradient Boosted tree; GRU: Gated recurrent units; HR = Heart Rate; IMU = Inertial Measurement Unit; ISO = International Organization for Standardization; KIM-MHO=Key Indicator Method for Manual Handling Operations; KNN = K-Nearest Neighbor; LR = Linear Regression; LSTM = Long Short-Term Memory; LVQ = Learning Vector Quantization; ML= Machine Learning; N.A. = Not Available; NB= Naive Bayes; NIOSH = National Institute for Occupational Safety and Health; OCRA = Occupational Repetitive Actions; OSHA = Occupational Safety and Health Administration; OWAS = Ovako Working Posture Analysis System; PERA = Postural Ergonomic Risk Assessment; REBA = Rapid Entire Body Assessment; RaF = Random Forest; RGB= red, green, blue; RNLE = Revised NIOSH Lifting Equation; RNN= Recurrent neural network; RoF = Rotation Forest; RULA = Rapid Upper Limb Assessment; SVM = Support Vector Machine; WS= wearable sensors.

units (GRU), Artificial Neural Networks (ANN), Naïve Bayes (NB) classifiers, Recurrent neural network (RNN), Convolutional Neural Network (CNN), and Learning Vector Quantization (LVQ).

In terms of accuracy, several algorithms showed high values. Among the ensemble classifiers, RaF was the best algorithm showing accuracy values above 90%. According to Antwi-Afari et al. (2020), the accuracy in identifying activities related to overextension was 97%. On the other hand, Manjarres et al. (2019) reported an accuracy of 97.7% in identifying activities performed by volunteer participants. The best results for KNNs in the classification of hand-arm transmitted vibration exposure in terms of accuracy (98%) were reached by Aiello et al. (2022). Another strong result is obtained from Antwi-Afari et al. (2022), detecting awkward posture using GRU and reaching an accuracy of 99%. Olsen et al. (2009) achieved an accuracy rate of 99.94% using a KNN algorithm to categorize postures as ergonomically correct or incorrect.

CONCLUSION

This article presents a narrative review of the use of AI for WMSD prevention purposes, selecting 28 relevant studies from the scientific literature. The analysis highlighted a deep interest, which has grown in recent years, in using AI algorithms (mainly ML and DL) to monitor the physical risk factors to which workers are exposed during their activities. This review provides the researchers with a summary of the most recent applications of AI to reduce the risks of developing WMSDs.

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